Should One Hire a Corrupt CEO in a Corrupt Country?

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Abstract

This paper examines the interaction between the propensity to corrupt (PTC) and firm performance. Using a unique data set of Moscow traffic violations, I construct the PTC of every Muscovite with a driver's license. Next, I determine the PTC for the top management of 58,157 privately held firms. I find that a one standard deviation increase in management PTC corresponds to a 3.6% increase in income diversion and that firms with corrupt management significantly outperform their counterparts. This study contributes to the literature that characterizes corruption using objective (rather than perception-based) measures and provides evidence regarding the positive aspects of corruption at the firm level.

Keywords: Corruption, tax evasion, CEO, firm performance

JEL Codes: D73, G30, G34, G38, H11, H26

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1. Introduction

Do corrupt managers deliver superior firm performance? The answer to this question is unclear from a theoretical perspective. Corrupt managers can advance shareholder interest in several respects. For instance, they can evade more taxes, generating de facto money transfers from the government to a firm. Corrupt managers can also obtain more government contracts and remove business impediments by paying bribes. Leff (1964) and Huntington (1968) suggest that corruption may help to maneuver around bad laws and institutions. Additionally, Lui (1985) shows that bribery can be efficient in a queuing model if agents whose time has a higher value can use bribes to obtain a better place in line relative to other agents. However, corrupt managers may also use firm resources for their own private benefits and therefore destroy shareholder value. Desai, Dyck, and Zingales (2007) document that an increase in tax enforcement in Russia, which decreased the private benefits of control extracted by company insiders, was followed by a positive market reaction. Mironov (2013) shows that income diversion not only leads to the transfer of money from shareholders to management but also deteriorates firm performance.

In this paper, I analyze the relation between managerial corruption and firm performance using micro-level data from Moscow firms. The key idea of the paper is that individual propensity to corrupt (PTC) can be inferred from recorded traffic violation data. Drivers occasionally commit traffic violations. However, not all traffic violations are recorded in corrupt countries. A driver who is stopped by police can often avoid a formal penalty in exchange for a bribe. Therefore, observing a person's recorded traffic violations for a long period of time allows an inference of individual propensity for corruption. To better understand my approach to PTC measurement, consider the following example. Two persons, A and B, have identical demographic characteristics, the same income level, and driving style. For some reason, however, driver A has a much higher number of recorded traffic violations than driver B. One possible explanation is that A is simply unlucky and that the police caught A every time that he or she was speeding. Another possible explanation is that A and B were stopped for approximately the same number of traffic violations but that B paid more police bribes than A and therefore has a lower number of recorded traffic violations.

Russia provides a unique environment in which to study corruption-related issues. Russia is the sixth largest economy in the world, with a per capita GDP of $23,549.[1] This figure is approximately equal to that of Eastern European countries, such as Hungary, Estonia, and Poland. However, the level of corruption in Russia is extremely high, similar to that of countries that are four to five times poorer. The 2012 Corruption Perceptions Index produced by Transparency International ranked Russia 133 out of 174 countries, slightly below Nicaragua, Uganda, Togo, and Honduras. In 2012, the World Bank's “Ease of Doing Business” index ranked Russia 112 out of 185 nations, slightly above El Salvador and Guyana

Data availability is another important factor that makes Russia a unique case. Russia inherited a comprehensive system of government statistics from the Soviet Union. Different administrative agencies routinely collect large amounts of data at the individual and firm levels. The data used in this paper cover the entire population of Moscow and all its firms, which range from small firms to extremely large firms. Thus, it is possible to conduct a comprehensive analysis of the economy with the size of a typical European country, such as Austria, Denmark, Greece, or Norway. It is difficult to imagine that such detailed data will become available for the U.S. or any Western economy in the near future. Several recent studies have built on this comparative advantage of the Russian statistical system.[2]

This paper makes three contributions to the literature. First, I develop an individual measure of corruption propensity for 3.1 million Muscovites (PTC). Second, I show that the PTC for firm management is positively related to income diversion and undeclared wages paid to employees.

[1] Source: WorldBank 2012 data

[2] See, for example, Braguinsky (2009); Braguinsky, Mityakov, and Liscovich (2010); Braguinsky and Mityakov (2013); Guriev and Rachinsky (2006); Mironov (2013); and Mironov and Zhuravskaya (2012).

Finally, I find evidence that there is a positive link between management PTC and firm performance measured as revenue growth, revenue per employee, and the ratio of revenue to assets. This paper is closely related to the rapidly growing body of literature on managerial malfeasance, including Desai, Dyck, and Zingales (2007); Johnson, La Porta, Lopez-de-Silanes, and Shleifer (2000); Bertrand, Mehta, and Mullainathan (2002); Mironov (2013); and Braguinsky and Mityakov (2013).

First, I build a measure of individual PTC based on the data on traffic violations, traffic accidents, and other personal characteristics, including gender, income, and distance to work, among others. The data on traffic violations and traffic accidents cover the city of Moscow and the surrounding region for the period from 1997 to 2007. The data contain information on 6,784,971 traffic violations and 159,054 traffic accident participants. The important difference between these two data sets is that nearly all traffic accidents are recorded, whereas the decision to record a traffic violation is determined by individual policemen, who are frequently bribed (in which case, the violation goes unrecorded). I estimate the expected number of recorded traffic violations for each driver, using driver demographic characteristics, personal income, driving distance to work, the number of traffic accidents in which the driver was involved, and car characteristics as the explanatory variables. The individual PTC measure is constructed based on the difference between the predicted number of traffic violations and the actual number of traffic violations. The economic intuition that stems from the expectation that a lower number of recorded traffic violations, given observable driver characteristics, indicates a higher probability that some traffic violations were not recorded in exchange for bribes. Using this approach, I build the measure of PTC for 3,136,839 Muscovites. Next, I determine management PTC for a sample of 58,157 firms and 145,695 firm-years during the 1999-2004 period. The PTC for a given company is estimated as the average of the individual PTC figures of the company's five best paid employees.

Second, I analyze the relation between PTC and existing metrics of managerial malfeasance, such as the income diversion measure developed by Mironov (2013) and the personal income transparency measure developed by Braguinsky and Mityakov (2013). The measure of income diversion is based on transfers to illegitimate fly-by-night firms. The money that is transferred to these firms represents a combination of tax evasion and managerial diversion. I find that PTC and illegitimate transfers are positively related. A one standard deviation increase in management PTC corresponds to a 0.3% firm revenue increase in income diversion (on average, each firm transfers 8.7% of its revenue to fly-by-night firms).

I also examine the relation between PTC and the measure of personal income transparency developed by Braguinsky and Mityakov (2013), based on the assumption that it is relatively easy to misreport earnings but costly to drive an unregistered vehicle. Thus, a person’s unreported income can be inferred from the discrepancy between his or her reported income and value of the car he or she owns. I find that firm management PTC and income transparency are negatively related. A one standard deviation increase in PTC is associated with a 7% decrease in reported income, holding car value constant.

Finally, I analyze the relation between management PTC and firm performance. Measuring firm performance is challenging if firms are involved in income diversion activities. Traditional measures based on earnings, such as ROA or ROE, cannot be applied. Thus, I employ revenue growth, revenue per employee, and the ratio of revenue to assets as measures of firm performance. I find that these measures and management PTC are positively related. A one standard deviation increase in management PTC corresponds to a 2.1% increase in the annual revenue growth rate, a 2.5% increase in revenue per employee, and a 0.5% increase in the ratio of revenue to assets. I provide several robustness tests of the latter results. First, I use bank receipts rather than revenue as a performance measure. Corrupt management may underreport a firm’s true revenue, and bank receipts may thus be a more accurate indicator of firm performance. The results are similar: increases in bank receipt figures, bank receipts per employee, and the ratio of bank receipts to assets are positively related to firm management PTC. Another robustness check pertains to companies that do not own cars. CEOs commonly use chauffeurs provided by firms. These CEOs will have a low number of traffic violations and therefore a spuriously high PTC. Eliminating CEOs with chauffeurs from the sample, the results are unchanged. As a final robustness check, I examine firm performance and alternative measures of corruption. Using income diversion measures developed by Mironov (2013) and the income transparency measure developed by Braguinsky and Mityakov (2013), I find a positive relation between all three measures of firm performance and the two alternative measures of corruption.[3]

Next, I analyze the firms that experience a change of CEO during the sample period. Similarly to Bertrand and Schoar (2003), I require that each CEO serves for at least two years. This selection criterion yields a subsample of 1,027 firms and 5,188 firm-years. I estimate the relation between firm performance and CEO PTC by introducing firm fixed effects in the regressions. I find a positive and statistically significant relation for two of three firm performance measures: the log of revenue per employee and the log of the ratio of revenue to assets. It is important to note that managers are not randomly allocated to firms. Therefore, the results presented in this paper should not be interpreted as causal effects of managerial corruption on firm performance, even under the specifications that include firm fixed effects.

Finally, I study the relation between firm ownership and the observed positive link between PTC and firm performance. I find that firms in which the CEO is the sole owner exhibit better performance than firms in which the CEO is not the sole owner. However, the relation between PTC and firm performance does not differ between these groups of firms. Nevertheless, I find

[3] Note that wage transparency is an inverse measure of corruption. Higher levels of wage transparency are associated with lower shares of “black” wages.

that the positive link between PTC and firm performance is not present in the sub-sample of foreign-owned firms. A possible explanation of this empirical finding may be that foreign owners restrict the corrupt behavior of their managers.

There may be several alternative explanations of the findings presented in this paper. For instance, differences in PTC may be due to differences in driving style. In particular, drivers with high PTC may be notably conscientious[4], whereas conscientious people may tend to be both good drivers and good managers. In view of the absence of statistical significance for the subsample of foreign-owned firms, it may be that foreign firms impose stricter hiring criteria than domestic firms and therefore hire conscientious managers rather than corrupt ones. Unfortunately, the available data do not allow us to discriminate between these alternative explanations.

This paper contributes to the rapidly growing literature that focuses on providing systematic evidence of corruption using objective (rather than perception-based) measures.[5] Reinikka and Svensson (2004) and Olken (2006) evaluate corruption by comparing the amount of federal grant transfer disbursements measured at the source to the amount that actually reaches the intended grant recipients. Caselli and Michaels (2009) estimate corruption by examining the effect of revenue windfalls across Brazilian municipalities. Bertrand, Djankov, Hanna, and Mullainathan (2007) and Olken (2007) measure corruption using randomized incentive schemes for corrupt behavior. Mironov and Zhuravskaya (2012) estimate corruption based on the linkage between shadow financing for election campaigns and the distribution of procurement contracts. Fisman and Miguel (2007) relate the number of unpaid parking tickets received by UN diplomats to country-level corruption norms.

[4] I would like to thank an anonymous referee for suggesting this interpretation.

[5] See, for example, Reinikka and Svensson (2006) for difficulties in the design of surveys to measure corruption.

By examining the relation between corruption and firm growth, this paper also contributes to the literature on the implications of corruption for economic development. Shleifer and Vishny (1993) present an analytical framework that may explain why “in some less developed countries, corruption is so high and so costly to development.” Shleifer and Vishny (1994) analyze the economic effect of privatization and commercialization in the presence of corruption. Mauro (1995) provides evidence that corruption negatively affects growth based on a sample of 68 countries. Shleifer and Wei (2000) find a negative relation between corruption and foreign direct investment (FDI). Kaufmann and Wei (1999) show that “firms that pay more bribes are also likely to spend more, not less, management time with bureaucrats negotiating regulations, and face higher, not lower, cost of capital.”

The remainder of the paper is structured as follows. Section 2 describes the data. Section 3 discusses the PTC measure. Section 4 presents the empirical results, and Section 5 concludes the paper.

2. Data and sample

This paper relies on several data sources (banking transaction data, personal income data, traffic violation data, and other data) leaked to the public domain from the Russian Central Bank and other government-affiliated entities. Appendix B discusses the legitimacy of these data.

2.1. Traffic violations, traffic accidents, and personal income data

The main data set that is used in this research is the list of traffic violations in the city of Moscow and the region of Moscow (Moscow oblast). This database contains 6,784,971 violations from the period from 1997 to 2007. Each entry includes the violation date and the violator’s identification data: his or her name, driver’s license, and date of birth. Some records include a description of the violation. Unfortunately, the data quality does not allow classification by type of traffic violation. During the studied period, parking tickets were rarely enforced in Moscow; thus, parking tickets represent only a tiny fraction of the total violations registered in the database.[6] The data for traffic accidents are available only for the city of Moscow. The data include information on 159,054 records. When multiple drivers were involved in an accident, the data include information for every driver. Each entry includes driver identification information (name, address, date of birth, and driver's license), the date, whether the driver was intoxicated, whether the driver fled the scene, driver culpability for the accident, and additional information.

I merge the data on traffic violations and traffic accidents with information from the database of issued driver's licenses. The data for the city of Moscow include information on 2,754,649 unique drivers. The data for the Moscow region include information regarding the driver's licenses of 2,154,104 individuals. Both data sets cover the time period through 2007.

These data are supplemented with the city of Moscow's auto registration database for 2005, which also contains retrospective data. Each entry contains information regarding the vehicle (make, model, and year) and its owner (person name or company name, address, and identification number) in addition to the record date. The database contains more than 11 million records. There can be multiple records per person (company) if a person (company) owns, or has ever owned, more than one car.

I obtain employment information from the personal income data of Moscow residents. This data set contains 55 million records for the 1999-2004 period—approximately 9 million records per year. Each entry contains unique identification data (name, address, and identification number) for both an employer and an employee. There can be multiple records per person if a person receives income from several sources. Guriev and Rachinsky (2006) use these data to measure income inequality when the data set includes super-rich individuals. Braguinsky,

[6] There are two primary reasons for this situation. The first reason is a parking fine cost of approximately $3, which is much lower than fines for other violations. The second reason is that Russian law previously required that all tickets be given in person. A policeman must have been waiting for a violator to give him or her the ticket. The situation has changed in 2012. The cost of a parking ticket in Moscow increased to $100, and policemen are no longer required to personally hand over parking tickets.

Mityakov, and Liscovich (2010) and Braguinsky and Mityakov (2013) use these data combined with the auto registration database to estimate the hidden earnings of Muscovites.

Merging driver's license data with the data set of personal income yields a sample of 3,136,853 persons. Table A1 presents the summary statistics. All variables are winsorized at the top 99% percentile. An average driver commits 0.115 traffic violations per year and participates in 0.003 traffic accidents per year. A total of 54% of persons are from the city of Moscow, and 74.1% of drivers are men. The average driver is 38.9 years old and has 3.3 years of driving experience. Russian law states that a driver's license should be renewed every 10 years. To estimate driving experience, I use the earliest driver's license present in the database. Missing previous driver's license data would lead us to underestimate an individual's driving experience. The average person earns $6,640 per year and travels 15.2 kilometers to work. Distance to work is calculated as a straight line between one's home zip code and his or her employer's zip code. I collect employer zip code-employee zip code pairs for 2,213,789 observations. Furthermore, 36% of drivers own a car. This percentage is low because the auto registry database is available only for the city of Moscow. Thus, 65% of residents in the city of Moscow own a car, and only 2% of residents in the Moscow region have a car. The average car is 6.77 years old, with a 98.2 horsepower engine.

2.2. Sample of companies

Company financial data are obtained from Rosstat, an official Russian statistical agency. This database contains information on company identification, names, addresses, dates of incorporation, industry, directors, owners, and basic accounting data, such as information on revenue, profits, net income, assets, and debt. According to Russian law, all firms (even small firms) must submit quarterly reports with balance sheets and income statements to Rosstat. Rosstat contains accounting data for approximately 2.5 million Russian firms.

I supplement company-reported financial data with the list of banking transaction for the six years between 1999 and 2004; this list was leaked to the public by the Russian Central Bank in 2005. See Mironov (2013) for a detailed description of these data and of numerous authenticity checks. The data set contains 513,169,660 transactions involving 1,721,914 business and government entities with information on the date of each transaction and the payer, recipient, amount, and purpose.

Using the personal income data for Moscow residents, I select all firms that have at least 10 employees. Next, I match this sample of firms to the Rosstat data and include companies that reported revenue greater than $100,000. I impose these restrictions to avoid including tiny firms that might not accurately report their financial data, and this method yields a sample of 60,402 companies and 156,373 company-years for 1999-2004. I calculate revenue growth as $\Delta Revenue_t = \log(Revenue_{t+1}) - \log(Revenue_t)$. Note that all variables are taken as reported and are not adjusted for inflation.

Table A2 describes the summary statistics of a company sample. The average (median) company has assets of $6,924K ($180K), revenue of $6,217K ($522K), and pre-tax earnings of $536K ($9K). The average (median) revenue growth is 11.8% (16.1%) per year. Employment data are obtained from the Moscow personal income database. The average (median) company has 122 (32) employees. Company bank receipts are obtained from the banking transaction data. The average (median) bank receipts are $6,863K ($390K). I follow Mironov (2013) and estimate income diversion for every firm in the sample. The average (median) company transfers 8.7% (2.2%) of its revenue to fly-by-night firms. Appendix C describes the identification of “fly-by-night” firms in detail. To minimize the effects of outliers on the results, revenue growth, revenue per employee, the ratio of revenue to assets, and leverage are winsorized at the top and bottom 5% level. All variables are defined and explained in Appendix D.

3. Measuring propensity to corrupt

3.1. Empirical strategy

I construct a measure of PTC based on traffic violation, traffic accident, demographic and other personal data. The idea behind this measure derives from the observation that not all actual traffic violations are recorded. Previous survey results presented by Levin and Satarav (2000) show that the Russian police force is a highly corrupt entity. It is almost always possible to avoid formal punishment for a traffic violation with a bribe. Traffic accident reporting is handled differently. Russian law requires that all traffic accidents be reported to the police, which essentially means that the parties involved in a traffic accident cannot amicably resolve the issue without informing the police. If one party leaves the scene of an accident, then the other party can always inform the police that the first party has done so. In this scenario, the first party will automatically be considered culpable for the accident. Even if the parties reach an agreement about accident culpability, they should wait for police officers to record the terms of agreement. As a result, unlike traffic violations, nearly all traffic accidents are recorded in the police database. To build an individual corruption attitude measure, I estimate the following model:

$$Violations_d = f\left(\alpha + \beta Controls_d + \nu_d\right), \tag{1}$$

where d is the driver index, $Violations_d$ is the number of recorded traffic violations per year and $Controls_d$ is a set of driver-level controls, including traffic accidents, demographic characteristics, car characteristics and other variables. Note that the number of traffic violations is a count non-negative variable. Thus, I use a Poisson regression to fit this model.

The difference between $Violations_d$ and $f\left(\alpha + \beta Controls_d\right)$ reflects the discrepancy between the expected number of recorded traffic violations and the actual number of recorded traffic violations.[7] I sort all drivers in descending order according to this difference and assign a continuous measure of PTC_d that varies from zero to 10, where zero represents the least "corrupt" driver in Moscow and 10 represents the most "corrupt" driver in Moscow. If $PTC_i = 9$, then 90% of Moscow drivers have a residual ν_d that is greater than ν_i. Intuitively, a lower number of recorded traffic violations, for a given number of observed personal characteristics, indicates a greater probability that the traffic violations were not recorded in exchange for a bribe.

Next, I construct the PTC measure of firm management. Because the personal income data do not reveal job titles, I select the five best-paid employees in each firm. CEOs, deputy CEOs, CFOs, and chief accountants likely number among the best-paid employees in every company. Then, I calculate the average of the individual PTC measures for the best-paid employees who have driver's licenses:

$$PTC^f = \frac{\sum_{i=1}^{5} PTC_i^f}{\sum_{i=1}^{5} I\left(d_i \in Drivers\right)}, \tag{2}$$

where *f* is the firm index, *i* is the employee index (employees are sorted based on their annual pay), PTC_i^f is the PTC for employee *i* who works at firm *f*, and $I\left(d_i \in Drivers\right)$ is an indicator function that equals one if employee *i* belongs to the set of drivers (i.e., has a driver's license). If an employee does not have a driver's license, then his or her PTC cannot be evaluated using the methodology that is described here. Therefore, I exclude those employees from my calculations of firm PTC. For robustness checks, I also estimate the PTC for the highest-paid employee.

[7] Note that the expected number of recorded traffic violations differs from the expected number of traffic violations. The available data do not allow us to identify a control group of people who never pay bribes. Thus, the expected number of traffic violations cannot be estimated without additional assumptions.

I perform two robustness checks to validate the constructed measure. First, I analyze the relation between shadow transfers and firm PTC. To this end, I estimate the following regression:

$$ShadowR_t^f = \alpha + \beta PTC_t^f + \gamma Controls_t^f + \theta_t + \varepsilon_t^f \,, \tag{3}$$

where *t* is the time index and *f* is the firm index. $Controls_t^f$ is a set of firm-level controls, θ_t are year fixed effects, ε_t^f is the error term, and $ShadowR_t^f$ is the amount of firm transfers to fly-by-night firms divided by firm revenue. Mironov (2013) shows that *ShadowR* is a reliable measure of income diversion, which includes tax evasion and managerial diversion. If corrupt managers divert more income, then we should expect $\beta > 0$.

Another robustness check relates PTC to the measure of wage transparency derived by Braguinsky and Mityakov (2013). Braguinsky's and Mityakov's measure of wage transparency is based on the difference between a person's reported income and the value of the car that he or she drives. This approach is founded on the observation that it is relatively easy to misreport earnings but costly to drive an unregistered vehicle. Thus, the discrepancy between reported income and car value reflects a person's unreported income. Braguinsky and Mityakov measure income transparency at a personal level:

$$Transparency_t^i = \log\left(Income_t^i\right) - \frac{1}{\lambda}\log\left(Car_t^i\right), \tag{4}$$

where *t* is the time index and *i* is the person index. $Income_t^i$ is a person's reported income, Car_t^i is the dollar value of the person's car, and λ is the demand elasticity for cars estimated at 0.35. I analyze the relation between wage transparency and PTC by estimating the following regression:

$$Transparency_t^f = \alpha + \beta PTC_t^f + \gamma Controls_t^f + \theta_t + \varepsilon_t^f \,, \tag{5}$$

where *t*, *f*, $Controls_t^f$, θ_t, and ε_t^f are the same as in equation (3) and where $Transparency_t^f$ is the wage transparency calculated as the average wage transparency of the employees of firm *f*. The validity of PTC implies that $\beta < 0$ because, *ceteris paribus*, more corrupt firm management is associated with higher unreported earnings of firm employees and higher levels of wage transparency.

3.2. Summary statistics of PTC measures

I estimate equation (1) to construct the individual PTC measures. Driver-level controls include traffic accidents, gender, age, driving experience, distance to work, the logarithm of income, a dummy for whether a driver is from the city of Moscow, a dummy for whether a driver owns a car, car horsepower, and car production year. Column (1) of Table 1 presents the estimation results for the entire sample (base specification). As the table data indicate, the number of traffic violations is negatively related to driver age, driving experience, and income. Men commit 0.089 more traffic violations than women. The number of traffic accidents and traffic violations are positively related, with one traffic accident associated with 0.0936 more traffic violations per year. Residents of the city of Moscow commit 0.077 fewer traffic violations than residents of the region of Moscow. One possible explanation may be that people from the city of Moscow use public transportation more frequently. Distance to work and the number of traffic violations are positively related. An additional kilometer of travel yields 0.0004 more traffic violations per year. The coefficient for the logarithm of income has a negative sign. A possible explanation is that richer people may place a higher value on time. Formal punishment requires spending time in a bank to pay a fine and arriving at a local police office to retrieve one's driver's license after it has been retained by the police. Thus, people whose time has high value may prefer to resolve problems informally. Columns (2)–(5) contain estimations for equation (1) for different subsamples. Column (2) includes only drivers from the city of Moscow. Column (3) presents the subsample of drivers for whom the distance to work was determined. Column (4) contains data only for Moscow car owners. Column (5) includes only drivers who have experienced traffic accidents.

[Insert Table 1 here]

Next, I use formula (2) to calculate PTC for firm management. Table 2 reports the summary statistics. PTC denotes the propensity to corrupt for the entire sample of drivers. PTC(N) for N={2,..5} denotes the propensity to corrupt for the corresponding subsample of drivers previously defined. As the table data indicate, the PTC for the top 5 highest-paid employees is 4.47, which is less than the average for the entire Moscow population (the average PTC for the Moscow population is 5, by design). The PTC top 5 for the other subsamples of drivers (PTC(2)-PTC(5)) varies from 4.64 to 4.82.

[Insert Table 2 here]

3.3. Verification of the measure

The underlying assumption of the PTC measure is that the difference between the expected number of traffic violations and the recorded number of traffic violations reflects the personal PTC. However, there may be many alternative explanations for the results. For example, this calculation could measure "luck," reflecting that some drivers are caught more often than others. Another possible explanation is that drivers with low PTC drive more often; thus, they have a higher number of recorded traffic violations. In this case, the PTC would reflect how often a person uses his or her car. There could be some other unobservable variable that explains why some drivers have a higher or lower number of recorded traffic violations, for example, drivers' caution or skill. Thus, it is important to analyze the relations among PTC and established measures of managerial malfeasance. I relate PTC to two different measures: shadow transfers to fly-by-night firms and wage transparency. I estimate equations (3) and (5) using the *debt/assets*, industry, tax district, assets and revenue decile dummies as control variables. Table 3 presents the results. As the data in columns (1) and (2) indicate, there is a positive statistically significant relation between firm management PTC and income diversion. A one standard deviation increase in the PTC top 5 corresponds to a 3.6% increase (0.3% of firm revenue) in shadow transfers (an average firm transfers 8.7% of its revenue to fly-by-night firms). The presented evidence supports the hypotheses that firm management PTC and income diversion are positively related. The results reported in columns (3) and (4) show that the PTC and wage transparency are negatively related (statically significant at the 1% level). A one standard deviation increase in PTC top 5 is associated with a 6.7% decrease in reported income when car value is held constant. This result indicates that managers with higher PTC pay a higher percentage of employee wages under the table.

[Insert Table 3 here]

4. PTC and firm performance

4.1. Empirical results

It is difficult to measure firm performance in a context of tax evasion and income diversion. Popular measures of firm performance such as ROA and ROE cannot be used; as shown in the previous section, the misreporting of earnings and firm management PTC are positively correlated. I cannot rely on the market-to-book ratio because the sample companies are not publicly traded. Therefore, I use revenue growth, revenue per employee, and the ratio of revenue to assets as measures of firm performance. To analyze the relation between PTC and firm performance, I estimate the following regression:

$$Performance_t^f = \alpha + \beta PTC_t^f + \gamma Controls_t^f + \theta_t + \varepsilon_t^f \, , \tag{6}$$

where t is the time index and f is the firm index. $Performance_t^f$ refers to revenue growth, the log of revenue per employee, or the log of the ratio of revenue to assets. $Controls_t^f$ is a set of firm-level controls, θ_t are year fixed effects, and ε_t^f is the error term.

Table 4 presents the estimation results for equation (6). The firm-level controls include *debt/assets*, industry, assets decile dummies, revenue decile dummies, and tax district dummies. According to the table data, PTC and firm performance are positively related. A one standard deviation increase in PTC top 5 corresponds to a 2.1% increase in annual revenue growth, a

2.5% increase in revenue per employee, and a 0.5% increase in the ratio of revenue to assets. All coefficients are statistically significant at the 1% level.

[Insert Table 4 here]

Note that the presented empirical results may have at least three alternative explanations. The first alternative is that corrupt managers misreport revenue and thus exhibit superior performance in the metrics based on revenue. Another explanation is that the suggested measures of corruption reflect other characteristics that are related to the quality of driving rather than to PTC. For example, drivers with high PTC may conscientious rather than corrupt, and one may expect that conscientious individuals are also good managers. Finally, many top managers commonly use personal chauffeurs, and these managers will have a low number of traffic violations and high PTC. I perform several robustness checks to test some of these alternative explanations.

4.2. Robustness checks

The first robustness check analyzes bank receipts rather than revenue. Companies can underreport their true revenues; thus, bank receipts may be a more accurate measure of performance than revenue is. I estimate equation (6) using bank receipt growth, bank receipts per employee, and the ratio of bank receipts to assets as dependent variables. The number of bank receipts is an objective measure that is derived from banking transaction data. I report the results in Table 5. As the table data show, the results do not change; firm management PTC is positively related to measures of firm performance. This relation is statistically significant at the 1% level. Notably, the magnitude of the coefficients in columns (3)-(6) is significantly larger than the magnitude of the similar coefficients reported in Table 4. This result supports the hypothesis that corrupt managers underreport their true performance; thus, the actual difference in performance measured as revenue per employee and the ratio of revenue to assets is even higher than the difference reported in Table 4.

[Insert Table 5 here]

The second robustness check examines whether the positive relation between PTC and firm performance results from the tendency of top managers to use chauffeurs rather than driving themselves. These managers have a low number of traffic violations and high PTC. This possible explanation could apply to the observed positive relation between PTC and firm performance: more successful managers, who tend to use chauffeurs, deliver superior firm performance. To test this hypothesis, I match the sample of companies with the city of Moscow auto registration database. I remove all companies that ever owned cars from the sample based on the assumption that a company that owns a car might give the CEO a car and a chauffeur, whereas if a company does not own a single car, then the CEO should not have a chauffeur. Granted, this exclusion does not ensure the elimination of all CEOs with chauffeurs from the sample; for instance, a company could lease a car for its CEO. However, according to the auto registration database, only 1,627 cars with engines greater than 100 horsepower belonged to leasing companies during the period under study. In total, the companies from my sample owned 16,918 cars. Thus, potential leasing represents only a small fraction of total car usage. Table A3 presents the summary statistics for the companies that do not own cars. The companies in this subsample are much smaller than the companies in the overall sample (see Table A2). An average (median) company has assets of $3,058K ($143K), revenue of $3,214K ($460K), and 92 (29) employees. Table A4 reports the estimation results for equation (6) for the subsample of firms without cars. As the table data indicate, the results are similar to those reported in Table 4; firm management PTC and firm performance are positively related.

The third robustness check uses PTC for different samples of drivers (see Tables I and II for reference). I estimate equation (3) using PTC(2)–PTC(5) as the dependent variables. Table A5 reports the estimation results.[8] The table data indicate that the results are similar to those reported in Table 4; firm performance and firm management PTC are positively related.

The fourth robustness check employs a cardinal measure of PTC instead of the ordinal measure used in this paper. Specifically, I assign the residual from equation (1) as the cardinal PTC for every driver and then estimate equation (6) using this measure. The firm-level controls include leverage, industry, decile dummies for assets and revenues, and tax district dummies. Table A6 presents the results. The table data indicate that the coefficients for cardinal PTC are positive and are statistically significant with respect to most specifications.

It is possible that the results obtained are driven by some other unobserved variable that correlates with an individual's driving style. Thus, the final robustness test relates firm performance to alternative measures of corruption that are unrelated to an individual's driving records. As alternative measures of corruption, I employ the income diversion measure developed by Mironov (2013) and the wage transparency measure developed by Braguinsky and Mityakov (2013). Table 6 presents the estimation results. As the table data indicate, the firm performance measures are positively related to income diversion and negatively related to wage transparency. The corresponding coefficients are statistically significant in five of six specifications.

[Insert Table 6 here]

One should interpret the OLS estimations presented in Table 6 with caution, as the relation between alternative measures of corruption and firm performance may be endogenous. Both measures of corruption–*ShadowR* and income transparency–reflect tax evasion. As Mironov (2013) observes, Russian entrepreneurs often prefer to register their businesses with tax agencies with which they have strong connections. Therefore, such firms may exhibit higher levels of tax evasion and stronger firm performance, owing to a more "favorable" business environment. The

[8] To save space, I report the results for PTC Top 5 only. The estimation results for PTC Top 1 are similar.

extreme case of such an endogenous relation is that of Yelena Baturina, the wife of the former mayor of Moscow, Yuri Luzhkov. According to *Forbes*, in 2010, she was the richest woman in Russia and the third richest woman in the world, earning her fortune when her husband was mayor. Milov and Nemtsov (2010) describe Luzhkov as highly corrupt, noting that he allocated significant budget resources to Inteko, the company owned by his wife. After his dismissal, her fortune fell from $2.9 billion in 2010 to $1.2 billion in 2011. There is also an endogeneity issue that acts in the opposite direction. The measure of income diversion, *ShadowR*, includes managerial diversion–concealment from firm owners and tax evasion–concealment from tax authorities. Desai, Dyck, and Zingales (2007) and Mironov (2013) argue that managerial diversion has a strong negative effect on firm performance.

These robustness checks cannot exclude all possible alternative explanations related to driving style. For example, it is possible that safe drivers exhibit a high PTC and are also good managers. Unfortunately, as shown in Table 1, the variable *Accidents*, which is an objective measure of driving safety, explains only a small fraction of the variance of *Violations*. Hence, the available data do not allow us to distinguish between safe and corrupt drivers.

4.3. Are manager characteristics relevant?

The results reported in Table 4 do not distinguish the effect of managers from the effect of the firms that they managed. In fact, some firms may have better growth prospects and attract more corrupt managers. There are two important papers that study the effect of managers on organization performance. First, Bertrand and Schoar (2003) show that manager effects are relevant for a wide range of corporate decisions, including investment, financial, and organizational practices. Second, the recent study of Lazear, Shaw, and Stanton (2012) provide a comprehensive analysis of various aspects of supervisor effects on worker productivity. The authors not only apply a basic fixed effects analysis but also employ mixed effects estimation, control for lagged boss effects, and test for non-random boss assignment.

My panel includes only six periods, with the average firm present in approximately 2.6 periods. Therefore, I follow the rationale behind the methods of Bertrand and Schoar (2003). Specifically, I study firms that experienced CEO turnover during the period of 1999-2004. Only CEOs with defined PTC are selected for this analysis. In addition, I require that each CEO manage a firm for at least two years.[9] These selection criteria yield a subsample of 1,027 firms and 5,188 firm-years. Then, I estimate equation (6) by including firm fixed effects. Panel A of Table 7 presents the estimation results. As the table data indicate, the coefficients for PTC are statistically insignificant for the revenue growth measure (columns (1)–(3)) and are positive and statistically significant for the log of revenue per employee and the log of the ratio of revenue to assets measures (columns (4)–(6) and (8)–(9)). Using ideas from the work of Lazear, Shaw, and Stanton (2012), I introduce a control for the influence of previous CEOs. Panel B of Table 7 includes a control for the lagged dependent variable, and Panel C of Table 7 includes a control for the lagged CEO's PTC. The results change very little: the coefficients for PTC in the revenue growth specification are statistically insignificant, and the coefficients for PTC in the specifications for the two remaining measures of firm performance are positive and statistically significant (with exception of the column (7) specification, where assets and revenue decile dummies are included simultaneously, and the log of the ratio of revenue to assets serves as a dependent variable).

[Insert Table 7 here]

In addition, I employ the alternative approach of Bertrand and Schoar (2003), namely, to estimate CEO fixed effects. Specifically, I select individuals who served as CEOs at multiple firms and worked at each of these firms for at least two years.[10] I also require that each firm

[9] By analogy with Bertrand and Schoar (2003), this two-year requirement ensures that managers are given an opportunity to "imprint their mark" on a given company.

[10] Bertrand and Schoar (2003) require that every manager serves at each company for at least three years. However, their panel contains 31 years (from 1969 to 1999), whereas my sample period has only six years (from 1999 to 2004). Applying the three-year criterion of Bertrand and Schoar (2003) leads to a sample of only 16 CEOs.

managed by these CEOs must also be managed by at least one other CEO. If a firm were managed by only one CEO, then the CEO fixed effect would be indistinguishable from the firm fixed effect. This selection criterion yields a sample of 94 CEOs. For each firm in which these CEOs worked, I retain all observations. The resulting sample contains 184 firms and 789 firm-year observations. I then estimate the following regressions:

$$Performance_t^f = \alpha + \phi_f + \gamma Controls_t^f + \lambda_{CEO} + \theta_t + \varepsilon_t^f , \tag{7}$$

where *t* is the time index and *f* is the firm index. $Performance_t^f$ is revenue growth, the log of revenue per employee, or the log of the ratio of revenue to assets. $Controls_t^f$ is a set of firm-level controls that includes *debt/assets*, industry, assets decile dummies, revenue decile dummies, and tax district dummies; θ_t are year fixed effects; ϕ_f are firm fixed effects; λ_{CEO} are CEO fixed effects; and ε_t^f is the error term. After obtaining the CEO fixed effects for three measures of firm performance from regression (7), I estimate the following regression:

$$FE\_Performance_{CEO} = \alpha + \beta PTC_{CEO} + \varepsilon_{CEO} , \tag{8}$$

where $FE\_Performance_{CEO}$ are the CEO fixed effects (λ_{CEO}) for different measures of firm performance (revenue growth, the log of revenue per employee, and the log of the ratio of revenue to assets) obtained in regression (7), PTC_{CEO} is the PTC for *CEO,* and ε_{CEO} is the error term. I use a GLS estimation technique to account for the measurement error in the left-hand-side variable. All observations are weighed by inverse standard error on the CEO fixed effect variable, which I obtain in the first step regressions. The results are as follows. All β coefficients are statistically insignificant for all three measures of performance.[11] A possible explanation for the absence of significance may be the short panel with a small sample of CEOs who served in multiple firms.

[11] The detailed results of this test are available upon request.

To summarize the results of this subsection, we cannot reach an unambiguous conclusion as to whether corrupt CEOs can carry their abilities across firms. The results presented in Table 7 indicate that the coefficients on PTC are positive and statistically significant for two of three performance measures in the presence of firm fixed effects. However, the examination of the sample of CEOs who served on multiple firms does not provide any statistically significant result. Nevertheless, the positive relation between PTC and measures of firm performance in the presence of firm fixed effects does not imply the causality of this relation because CEOs are not assigned to firms randomly and because their movement across firms is not random.

4.4. Is ownership relevant?

The results reported in Tables 3 and 4 are not conclusive regarding the benefits to company owners of hiring a corrupt manager. Corrupt managers divert more income and have a lower level of transparency than non-corrupt managers; however, managers with a high PTC are also associated with superior performance in terms of revenue growth and revenue per employee. Therefore, a question arises as to whether the latter effect depends on company ownership. The relationship between managers and shareholders is subject to agency costs (see Jensen and Meckling, 1976, for a detailed discussion of the manager-shareholder conflict). These costs could significantly deteriorate the possible benefits of managerial corruption for firm performance. To analyze the possible effect of manager-shareholder agency costs, I estimate the following regression:

$$Performance_t^f = \alpha + \beta PTC_t^f + \gamma Ceo\_owner_t^f + \delta PTC_t^f Ceo\_owner_t^f + \phi Controls_t^f + \theta_t + \varepsilon_t^f \text{ , (9)}$$

where t is the time index and f is the firm index. $Performance_t^f$ refers to revenue growth, the log of revenue per employee, or the log of the ratio of revenue to assets. $Ceo\_owner_t^f$ is a dummy variable that is equal to one if the CEO is the sole[12] owner of a company, $Controls_t^f$ is a set of firm-level controls, θ_t is year fixed effects, and ε_t^f is the error term.

Table 8 presents the estimation results for equation (9). As the table data indicate, firms whose CEOs are sole owners show superior performance (columns (1), (3), and (5)); however, the coefficients for the interaction of *PTC* and $Ceo\_owner_t^f$ are not significantly different from zero (columns (2), (4), and (6)). Based on this evidence, we cannot conclude that the effect of managerial corruption on firm performance differs between firms that are owned by CEOs and firms that are not owned by CEOs.

[Insert Table 8 here]

Another interesting question is whether foreign owners can restrict the corruption practices of their local managers. To study this question, I estimate equation (6) for the subsample of foreign-owned firms. Table 9 presents the results. As the table data indicate, the coefficients for PTC are statistically and economically insignificant in all specifications except column (2), in which the corresponding coefficient is marginally significant. This finding is consistent with those of Braguinsky and Mityakov (2013), who report that income transparency (measured as reported earnings when car values are held constant) is four times higher in foreign-owned firms than in domestic firms. Alternatively, it is also possible that foreign firms do not hire corrupt managers. Selection criteria in foreign firms are typically much stricter than in Russian firms. Therefore, managers of foreign firms may differ from managers of Russian firms.

[Insert Table 9 here]

5. Conclusion

This paper develops a novel method of measuring corruption at the individual level. I use a unique data set for Moscow traffic violations to infer the PTC for 3.1 million Muscovites.

[12] If a firm has a multiple owners, then the firm is subject to a manager-shareholder conflict even if a CEO is one of the owners. The CEO can expropriate other owners of the firm, thus deteriorating firm performance.

Based on individual PTC, I build a measure of PTC for the management of 58,157 privately held firms. I show that firms with corrupt management significantly outperform those without corrupt management. A one standard deviation increase in company management PTC is associated with a 2.1% increase in the annual revenue growth rate, a 2.5% increase in revenue per employee, and a 0.5% increase in the ratio of revenue to assets. However, corrupt managers divert more income, and their firms exhibit lower income transparency. A one standard deviation increase in PTC corresponds to a 0.3% increase in firm revenue transfers to fly-by-night firms.

I suggest several areas for future research. First, it is important to analyze whether PTC is constant or variable over time. For example, does government agency employment increase individual PTC? Conversely, does employment with a foreign company with high corporate governance standards decrease PTC? Another interesting research question may involve the career movement of employees across firms and within the same firm. Who has better opportunities for promotion—a more corrupt employee or a less corrupt employee? Finally, it is important to estimate the effect of corruption on talent allocation across different economic sectors.

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Table 1. Traffic Violations and Traffic Accidents

The table presents Poisson regressions of the number of traffic violations on traffic accidents and other driver-level controls. The sample period is from 1997 to 2007. Marginal effects are reported. *Traffic violations per year* is the average number of traffic violations per year committed by an individual in the city of Moscow and Moscow region. *Traffic accidents per year* is the average number of traffic accidents per year committed by an individual in the city of Moscow. *Driver is from Moscow* is a dummy variable equal one if the person resides in the city of Moscow. *Male* is a dummy variable equal one for men and zero for women. *Driver's age* is calculated as the average driver's age. *Driving experience* is the average driving experience. *Income* is the average person's income taken from the personal income data of Moscow residents. *Distance to work* is calculated as a straight line between person's home zip code and his or her employer zip code averaged over the sample period. *Distance to work* is obtained for 2,235,680 observations. *Driver owns a car* is a dummy variable equal one if the person ever owned a car during the sample period (car registry data are available only for the city of Moscow). *Car age* and *Car power* are the average car age and car horse power calculated over the period when the person owned a car or cars. Column (1) contains the entire sample. Column (2) includes only drivers from the city of Moscow. Column (3) presents the subsample of drivers for which distance to work is determined. Column (4) contains only drivers from Moscow which own a car. Column (5) includes only drivers with a positive record of traffic accidents. The numbers in parentheses are standard errors. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Dependent var:	Traffic violations per year				
	(1)	(2)	(3)	(4)	(5)
Traffic accidents per year	0.0936	0.0891	0.0914	0.0962	0.1208
	(0.0034)***	(0.0032)***	(0.0034)***	(0.0052)***	(0.0122)***
Driver is from Moscow	-0.0767		-0.0730		-0.1116
	(0.0005)***		(0.0006)***		(0.0055)***
Male	0.0894	0.0494	0.0747	0.0424	0.0873
	(0.0003)***	(0.0003)***	(0.0003)***	(0.0004)***	(0.0029)***
Driver's age (X100)	-0.2666	-0.1517	-0.2241	-0.1688	-0.3395
	(0.0011)***	(0.0012)***	(0.0012)***	(0.0016)***	(0.0136)***
Driving experience (X100)	-0.6090	-0.0299	-0.4103	-0.0295	0.0431
	(0.009)***	(0.0078)***	(0.0095)***	(0.0103)***	(0.091)
Dummy (Income>0)	0.0335	0.0241	0.0303	0.0261	0.0651
	(0.0005)***	(0.0005)***	(0.0006)***	(0.0007)***	(0.0049)***
Log(Income)	-0.0061	-0.0052	-0.0061	-0.0059	-0.0146
	(0.0001)***	(0.0001)***	(0.0001)***	(0.0001)***	(0.0011)***
Dummy (Distance to work>0)	-0.0230	-0.0115		-0.0040	-0.0261
	(0.0004)***	(0.0005)***		(0.0006)***	(0.0041)***
Distance to work (X100)	0.0412	0.0609	0.0378	0.0260	0.0624
	(0.0006)***	(0.0012)***	(0.0006)***	(0.0023)***	(0.0081)***
Driver owns a car	0.0000	0.0020	0.0013		-0.0356
	(0.0012)	(0.0008)***	(0.0012)		(0.0105)***
Car age (X100)	0.0385	0.0145	0.0313	0.0200	0.1872
	(0.0053)***	(0.0032)***	(0.0049)***	(0.0036)***	(0.0379)***
Dummy (Car power>0)	0.0043	-0.0004	0.0042	-0.0019	0.0280
	(0.004)	(0.0023)	(0.0037)	(0.0027)	(0.0273)
Log (Car power)	0.0005	0.0010	0.0004	0.0014	-0.0051
	(0.0008)	(0.0005)*	(0.0008)	(0.0005)***	(0.0059)
Pseudo R-sq	0.140	0.078	0.136	0.058	0.083
Number of obs	3,136,839	1,692,300	2,235,680	1,097,089	60,128

Table 2. Summary Statistics of PTC Measures

The table presents summary statistics of propensity to corrupt (PTC) measures defined in Section II. The sample period is from 1999 to 2004. *PTC(N) top 1* is the PTC for the companies' best paid employee. *PTC(N) top 5* is the average PTC for the companies' 5 best paid employees. Only employees with a driving license are considered while calculating companies' PTCs. PTC is estimated for the entire sample of drivers. PTC(2) is calculated only for drivers from the city of Moscow. PTC(3) is estimated for the subsample of drivers for which distance to work is determined. PTC(4) is calculated only for drivers from Moscow which own a car. PTC(5) is estimated only for drivers with a positive record of traffic accidents.

	Mean	Median	St. dev.	N of obs	N of firms
	(1)	(2)	(3)	(4)	(5)
PTC top 1	4.502	4.737	2.328	92,722	41,756
PTC top 5	4.477	4.419	1.654	145,695	58,157
PTC(2) top 1	4.853	5.425	2.675	77,318	35,395
PTC(2) top 5	4.758	4.739	2.049	136,051	55,182
PTC(3) top 1	4.669	5.021	2.478	88,896	40,387
PTC(3) top 5	4.635	4.599	1.784	143,485	57,635
PTC(4) top 1	4.816	5.073	2.663	69,765	32,303
PTC(4) top 5	4.815	4.771	2.177	127,067	52,159
PTC(5) top 1	4.532	4.697	2.267	2,479	1,421
PTC(5) top 5	4.721	4.782	2.326	8,693	5,064

Table 3. PTC, Shadow Transfers, and Wage Transparency

The table presents the relation of PTC to income diversion and wage transparency. The sample period is from 1999 to 2004. *ShadowR* is the measure of income diversion developed by Mironov (2013). See Appendix C for details. *Wage transparency* is the measure of income transparency developed by Braguinsky and Mityakov (2013). *Revenue, Debt, Assets* are taken from Rosstat. All other variables are defined in Table 2. The numbers in parentheses are robust standard errors, clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Dependent var:	ShadowR		Wage transparency	
	(1)	(2)	(3)	(4)
PTC top 1	0.0013		-0.0242	
	(0.0002)***		(0.0043)***	
PTC top 5		0.0019		-0.0404
		(0.0003)***		(0.0051)***
Debt/Assets	-0.0059	-0.0043	-0.6396	-0.6362
	(0.0024)**	(0.0019)**	(0.0458)***	(0.0381)***
Assets decile dummy	Y	Y	Y	Y
Revenue decile dummy	Y	Y	Y	Y
Industry dummy	Y	Y	Y	Y
Year dummy	Y	Y	Y	Y
Tax district dummy	Y	Y	Y	Y
R-sq	0.063	0.063	0.068	0.064
Number of obs	92,722	145,695	43,970	66,501
Number of firms	41,756	58,157	23,914	33,066

Table 4. PTC and Firm Performance

The table presents the relation of PTC to different measures of firm performance. The sample period is from 1999 to 2004. *Revenue, Debt, Assets* are taken from Rosstat. *Revenue growth* is defined as [log($Revenue_{t+1}$)-log($Revenue_t$)]. All other variables are defined in Table 2. The numbers in parentheses are robust standard errors, clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Dependent var:	Revenue growth		Log(Revenue per employee)		Log(Revenue/Assets)	
	(1)	(2)	(3)	(4)	(5)	(6)
PTC top 1	0.0077		0.0113		0.0022	
	(0.001)***		(0.0015)***		(0.0006)***	
PTC top 5		0.0124		0.0150		0.0032
		(0.0011)***		(0.0018)***		(0.0007)***
Debt/Assets	-0.0504	-0.0448	0.1907	0.2016	-0.0474	-0.0581
	(0.0118)***	(0.0094)***	(0.0167)***	(0.0141)***	(0.0084)***	(0.007)***
Assets decile dummy	Y	Y	Y	Y	Y	Y
Revenue decile dummy	Y	Y	Y	Y	Y	Y
Industry dummy	Y	Y	Y	Y	Y	Y
Year dummy	Y	Y	Y	Y	Y	Y
Tax district dummy	Y	Y	Y	Y	Y	Y
R-sq	0.033	0.031	0.579	0.577	0.895	0.894
Number of obs	78,039	122,434	92,722	145,695	92,722	145,695
Number of firms	35,100	48,948	41,756	58,157	41,756	58,157

Table 5. PTC and Firm Performance (Bank Receipts)

The table presents the relation of PTC to different measures of firm performance calculated based on the bank receipts. The sample period is from 1999 to 2004. *Revenue, Debt, Assets* are taken from Rosstat. *Receipts growth* is defined as [log($Receipts_{t+1}$)-log($Receipts_t$)]. All other variables are defined in Table 2. The numbers in parentheses are robust standard errors, clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Dependent var:	Receipts growth		Log(Receipts per employee)		Log(Receipts/Assets)	
	(1)	(2)	(3)	(4)	(5)	(6)
PTC top 1	0.0068		0.0302		0.0218	
	(0.0015)***		(0.0031)***		(0.0025)***	
PTC top 5		0.0088		0.0432		0.0331
		(0.0017)***		(0.0036)***		(0.003)***
Debt/Assets	-0.0107	0.0048	-0.1862	-0.1555	-0.4000	-0.3751
	(0.0182)	(0.0144)	(0.0358)***	(0.0299)***	(0.0298)***	(0.0248)***
Assets decile dummy	Y	Y	Y	Y	Y	Y
Revenue decile dummy	Y	Y	Y	Y	Y	Y
Industry dummy	Y	Y	Y	Y	Y	Y
Year dummy	Y	Y	Y	Y	Y	Y
Tax district dummy	Y	Y	Y	Y	Y	Y
R-sq	0.019	0.018	0.325	0.335	0.396	0.391
Number of obs	61,374	95,310	91,197	143,154	91,197	143,154
Number of firms	29,931	41,573	41,187	57,330	41,187	57,330

Table 6. Firm Performance, Income Diversion, and Wage Transparency

The table presents the relation of income diversion and wage transparency to different measures of firm performance. The sample period is from 1999 to 2004. *ShadowR* is the measure of income diversion developed by Mironov (2013). See Appendix C for details. *Wage transparency* is the measure of income transparency developed by Braguinsky and Mityakov (2013). *Revenue, Debt, Assets* are taken from Rosstat. *Revenue growth* is defined as [log($Revenue_{t+1}$)-log($Revenue_t$)]. All other variables are defined in Table 2. The numbers in parentheses are robust standard errors, clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Dependent var:	Revenue growth		Log(Revenue per employee)		Log(Revenue/Assets)	
	(1)	(2)	(3)	(4)	(5)	(6)
ShadowR	0.1797		0.5095		0.0693	
	(0.0145)***		(0.0196)***		(0.0088)***	
Wage transparency		-0.0004		-0.0432		-0.0066
		(0.0015)		(0.0023)***		(0.001)***
Debt/Assets	-0.0454	-0.0537	0.2084	0.2119	-0.0571	-0.0528
	(0.0091)***	(0.0132)***	(0.0138)***	(0.0203)***	(0.0068)***	(0.0101)***
Assets decile dummy	Y	Y	Y	Y	Y	Y
Revenue decile dummy	Y	Y	Y	Y	Y	Y
Industry dummy	Y	Y	Y	Y	Y	Y
Year dummy	Y	Y	Y	Y	Y	Y
Tax district dummy	Y	Y	Y	Y	Y	Y
R-sq	0.031	0.034	0.578	0.558	0.894	0.890
Number of obs	131,482	59,733	156,373	69,646	156,373	69,646
Number of firms	50,876	29,160	60,402	34,090	60,402	34,090

Table 7. PTC and Firm Performance with Firm Fixed Effects

The table presents the relation of PTC to different measures of firm performance controlling for firm fixed effects. Only firms which experienced a CEO turnover are included. The sample period is from 1999 to 2004. *Revenue, Debt, Assets* are taken from Rosstat. *Revenue growth* is defined as [log($Revenue_{t+1}$)-log($Revenue_t$)]. *PTC top 1* is the PTC for the companies' best paid employee. Panel A contains the basic specification. The panel B specification controls for lagged dependent variable. The panel C specification controls for lagged PTC. The numbers in parentheses are robust standard errors, clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Panel A. PTC and firm performance with firm fixed effects

Dependent var:	Revenue growth			Log(Revenue per employee)			Log(Revenue/Assets)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PTC top 1	0.0021	-0.0029	-0.0021	0.0099	0.0173	0.0162	-0.0008	0.0078	0.0122
	(0.0047)	(0.0053)	(0.0053)	(0.0035)***	(0.0048)***	(0.005)***	(0.0027)	(0.0046)*	(0.0054)**
Debt/Assets	0.0023	0.1521	0.1372	0.0601	-0.1696	-0.0875	-0.0784	-0.3329	-0.5290
	(0.0595)	(0.0662)**	(0.066)**	(0.0446)	(0.0615)***	(0.0633)	(0.0345)**	(0.0579)***	(0.068)***
Assets decile dummy	Y	Y		Y	Y		Y	Y	
Revenue decile dummy	Y			Y			Y		
Firm fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y
R-sq	0.396	0.243	0.238	0.925	0.855	0.844	0.946	0.845	0.784
Number of obs	4,290	4,290	4,290	5,188	5,188	5,188	5,188	5,188	5,188
Number of firms	845	845	845	1,027	1,027	1,027	1,027	1,027	1,027

Panel B. PTC and firm performance with firm fixed effects and lagged dependent variable

Dependent var:	Revenue growth			Log(Revenue per employee)			Log(Revenue/Assets)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PTC top 1	0.0035	-0.0020	-0.0012	0.0088	0.0158	0.0133	-0.0002	0.0093	0.0149
	(0.0053)	(0.0058)	(0.0058)	(0.0039)**	(0.0052)***	(0.0053)**	(0.003)	(0.0049)*	(0.0057)***
Lagged dependent var	0.0174	-0.1863	-0.1890	0.1010	0.1784	0.2087	0.0135	0.0338	0.0775
	(0.0188)	(0.0186)***	(0.0185)***	(0.0116)***	(0.0152)***	(0.0153)***	(0.0084)	(0.0136)**	(0.0159)***
Debt/Assets	0.0084	0.1585	0.1620	0.0927	-0.1294	-0.0718	-0.0822	-0.3415	-0.4943
	(0.0673)	(0.074)**	(0.0737)**	(0.051)*	(0.0675)*	(0.0688)	(0.0393)**	(0.063)***	(0.0739)***
Assets decile dummy	Y	Y		Y	Y		Y	Y	
Revenue decile dummy	Y			Y			Y		
Firm fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y
R-sq	0.424	0.295	0.293	0.932	0.879	0.873	0.950	0.870	0.819
Number of obs	3,590	3,590	3,590	4,151	4,151	4,151	4,274	4,274	4,274
Number of firms	845	845	845	1,027	1,027	1,027	1,027	1,027	1,027

Panel C. PTC and firm performance with firm fixed effects and lagged PTC

Dependent var:	Revenue growth			Log(Revenue per employee)			Log(Revenue/Assets)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PTC top 1	0.0035	-0.0022	-0.0015	0.0075	0.0162	0.0135	0.0004	0.0103	0.0172
	(0.0058)	(0.0065)	(0.0065)	(0.0043)*	(0.0058)***	(0.006)**	(0.0034)	(0.0054)*	(0.0065)***
Lagged PTC top 1	-0.0003	0.0023	0.0029	0.0097	0.0075	0.0084	-0.0006	-0.0029	-0.0052
	(0.0057)	(0.0064)	(0.0064)	(0.0043)**	(0.0057)	(0.0059)	(0.0033)	(0.0053)	(0.0063)
Debt/Assets	0.0192	0.1706	0.1731	0.0981	-0.1365	-0.0731	-0.0621	-0.3214	-0.4948
	(0.0706)	(0.0792)**	(0.0789)**	(0.0533)*	(0.0711)*	(0.0728)	(0.0415)	(0.0665)***	(0.0788)***
Assets decile dummy	Y	Y		Y	Y		Y	Y	
Revenue decile dummy	Y			Y			Y		
Firm fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year dummy	Y	Y	Y	Y	Y	Y	Y	Y	Y
R-sq	0.446	0.293	0.289	0.932	0.877	0.869	0.951	0.871	0.817
Number of obs	3,303	3,303	3,303	3,943	3,943	3,943	3,943	3,943	3,943
Number of firms	845	845	845	1,027	1,027	1,027	1,027	1,027	1,027

Table 8. PTC, Firm Performance, and Ownership

The table presents the relation of PTC to firm performance and ownership. The sample period is from 1999 to 2004. *CEO is the sole owner* is a dummy variable equal one if the CEO is also the sole firm owner. *Revenue, Debt, Assets* are taken from Rosstat. *Revenue growth* is defined as [log($Revenue_{t+1}$)-log($Revenue_t$)]. All other variables are defined in Table 2. The numbers in parentheses are robust standard errors, clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Dependent var:	Revenue growth		Log(Revenue per employee)		Log(Revenue/Assets)	
	(1)	(2)	(3)	(4)	(5)	(6)
PTC top 5	0.0117	0.0115	0.0147	0.0160	0.0034	0.0037
	(0.0012)***	(0.0013)***	(0.002)***	(0.0022)***	(0.0008)***	(0.0009)***
CEO is the sole owner	0.0065	0.0015	0.2057	0.2491	0.0255	0.0356
	(0.0064)	(0.0177)	(0.0102)***	(0.0253)***	(0.0039)***	(0.0102)***
PTC top 5x		0.0011		-0.0095		-0.0022
xCEO is the sole owner		(0.0036)		(0.005)*		(0.0021)
Debt/Assets	-0.0401	-0.0401	0.1797	0.1795	-0.0612	-0.0612
	(0.0102)***	(0.0102)***	(0.0157)***	(0.0157)***	(0.0078)***	(0.0078)***
Assets decile dummy	Y	Y	Y	Y	Y	Y
Revenue decile dummy	Y	Y	Y	Y	Y	Y
Industry dummy	Y	Y	Y	Y	Y	Y
Year dummy	Y	Y	Y	Y	Y	Y
Tax district dummy	Y	Y	Y	Y	Y	Y
R-sq	0.031	0.031	0.588	0.588	0.893	0.893
Number of obs	99,475	99,475	116,334	116,334	116,334	116,334
Number of firms	37,441	37,441	43,004	43,004	43,004	43,004

Table 9. PTC and Firm Performance: Foreign-owned Firms

The table presents the relation of PTC to different measures of firm performance for a sample of foreign-owned firms. The sample period is from 1999 to 2004. *Revenue, Debt, Assets* are taken from Rosstat. *Revenue growth* is defined as [log($Revenue_{t+1}$)-log($Revenue_t$)]. All other variables are defined in Table 2. The numbers in parentheses are robust standard errors, clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Dependent var:	Revenue growth		Log(Revenue per employee)		Log(Revenue/Assets)	
	(1)	(2)	(3)	(4)	(5)	(6)
PTC top 1	-0.0024		-0.0016		0.0061	
	(0.006)		(0.0086)		(0.005)	
PTC top 5		0.0094		0.0001		0.0031
		(0.0057)*		(0.0097)		(0.0046)
Debt/Assets	-0.0717	-0.0305	0.0632	0.0575	-0.0717	-0.1359
	(0.0498)	(0.0371)	(0.0661)	(0.0567)	(0.0453)	(0.0356)***
Assets decile dummy	Y	Y	Y	Y	Y	Y
Revenue decile dummy	Y	Y	Y	Y	Y	Y
Industry dummy	Y	Y	Y	Y	Y	Y
Year dummy	Y	Y	Y	Y	Y	Y
Tax district dummy	Y	Y	Y	Y	Y	Y
R-sq	0.078	0.053	0.652	0.640	0.810	0.803
Number of obs	2,814	4,885	3,317	5,757	3,317	5,757
Number of firms	1,294	1,880	1,538	2,237	1,538	2,237

Appendix A – Supplementary Tables

Table A1. Summary Statistics of Traffic Violations and Traffic Accidents Data.

The table presents summary statistics of traffic violations and traffic accidents data. The sample period is from 1997 to 2007. *Traffic violations per year* is the average number of traffic violations per year committed by an individual in the city of Moscow and Moscow region. *Traffic accidents per year* is the average number of traffic accidents per year committed by an individual in the city of Moscow. *Driver is from Moscow* is a dummy variable equal one if the person resides in the city of Moscow. *Male* is a dummy variable equal one for men and zero for women. *Driver's age* is calculated as the average driver's age. *Driving experience* is the average driving experience. *Income* is the average person's income taken from the personal income data of Moscow residents. *Distance to work* is calculated as a straight line between person's home zip code and his or her employer zip code averaged over the sample period. *Distance to work* is obtained for 2,235,680 observations. *Driver owns a car* is a dummy variable equal one if the person ever owned a car during the sample period (car registry is available only for the city of Moscow). *Car age* and *Car power* are the average car age and car horse power calculated over the period when the person owned a car or cars. Panel A presents the summary statistics for the entire sample. Panel B and Panel C describe the drivers from Moscow region and the city of Moscow accordingly.

	Mean	Median	St. dev.	N of obs
	(1)	(2)	(3)	(4)
Panel A. Entire sample				
Traffic violations per year	0.115	0	0.276	3,136,853
Traffic accidents per year	0.003	0	0.022	3,136,853
Driver is from the city of Moscow	0.539	1	0.498	3,136,853
Male	0.741	1	0.438	3,136,853
Driver's age	38.9	38.0	12.8	3,136,853
Driving experience	3.29	3.29	1.55	3,136,853
Income	6,640	3,328	10,418	3,009,121
Distance to work	15.2	8.8	19.0	2,213,789
Driver owns a car	0.358	0	0.479	3,136,853
Car's age	6.77	5.50	5.38	1,123,284
Car power (hp)	98.2	84.4	41.8	1,023,044
Panel B. Drivers from the Moscow region				
Traffic violations per year	0.184	0	0.361	1,444,539
Traffic accidents per year	0.001	0	0.017	1,444,539
Male	0.762	1	0.426	1,444,539
Driver's age	38.6	37.5	12.6	1,444,539
Driving experience	2.94	3.29	1.21	1,444,539
Income	5,593	3,100	8,098	1,383,218
Distance to work	29.1	20.8	25.4	755,440
Driver owns a car	0.018	0	0.133	1,444,539
Car's age	7.23	5.83	6.21	26,195
Car power (hp)	108.4	93.8	49.6	21,856
Panel C. Drivers from the city of Moscow				
Traffic violations per year	0.056	0	0.149	1,692,314
Traffic accidents per year	0.004	0	0.025	1,692,314
Gender	0.722	1	0.448	1,692,314
Driver's age	39.2	38.5	13.1	1,692,314
Driving experience	3.58	3.29	1.74	1,692,314
Income	7,532	3,541	11,973	1,625,903
Distance to work	8.0	6.3	7.9	1,458,349
Driver owns a car	0.648	1	0.478	1,692,314
Car's age	6.76	5.43	5.36	1,097,089
Car power (hp)	97.9	84.0	41.6	1,001,188

Table A2. Summary Statistics for the Sample of Companies

The table presents summary statistics for the sample of companies. The sample period is from 1999 to 2004. *Revenue, Assets, Earnings Before Taxes* and *Debt* are taken from Rosstat. *Number of employees* is calculated using the personal income data of Moscow residents. *Bank receipts* is the total cash receipts obtained from the banking transaction data. *ShadowR* is the measure of income diversion developed by Mironov (2013). See Appendix C for details. *Wage transparency* is the measure of income transparency developed by Braguinsky and Mityakov (2013). Variable growth is defined as [log$(Variable_{t+1})$-log$(Variable_t)$].

	Mean (1)	Median (2)	St. dev. (3)	N of obs (4)	N of firms (5)
Revenue, $000's	$6,217	$522	$232,643	156,373	60,402
Assets, $000's	$6,924	$180	$421,919	156,373	60,402
Earnings Before Taxes, $000's	$536	$9	$33,922	155,118	60,087
EBT / Revenue	0.041	0.016	0.079	155,118	60,087
Debt / Assets	0.111	0.000	0.225	156,373	60,402
Number of employees	122	32	1248	156,373	60,402
Revenue growth	0.118	0.161	0.614	131,482	50,876
Revenue per employee	$37.28	$14.67	$54.37	156,373	60,402
Revenue/Assets	6.348	3.401	7.689	156,373	60,402
Bank receipts	$6,863	$390	$449,895	156,373	60,402
Bank receipts growth	0.208	0.231	0.845	101,907	43,146
Bank receipts per employee	$33.67	$11.09	$53.83	156,373	60,402
Bank receipts/Assets	4.709	2.076	6.606	156,373	60,402
ShadowR	0.087	0.022	0.136	156,373	60,402
Wage transparency	-17.034	-16.864	1.777	69,646	34,090

Table A3. Summary Statistics for Companies without Cars

The table presents summary statistics for the subsample of companies which do not own cars. Car ownership data is taken from the Moscow city auto registration database. In addition, all companies with revenue greater than $1 billion assumed to have cars (i.e. provide chauffeurs for their CEOs). The sample period is from 1999 to 2004. *Revenue, Assets*, *Earnings Before Taxes* and *Debt* are taken from Rosstat. *Number of employees* is calculated using the personal income data of Moscow residents. *Bank receipts* is the total cash receipts obtained from the banking transaction data. *ShadowR* is the measure of income diversion developed by Mironov (2013). See Appendix C for details. Wage transparency is the measure of income transparency developed by Braguinsky and Mityakov (2013). Variable growth is defined as [log$(Variable_{t+1})$-log$(Variable_t)$]. *PTC(N) top 1* is the PTC for the companies' best paid employee. *PTC(N) top 5* is the average PTC for the companies' 5 best paid employees. Only employees with a driving license are taken into account while calculating companies' PTCs. PTC is estimated for the entire sample of drivers. PTC(2) is calculated only for drivers from the city of Moscow. PTC(3) is estimated for the subsample of drivers for which distance to work is determined. PTC(4) is calculated only for drivers from Moscow which own a car. PTC(5) is estimated only for drivers with a positive record of traffic accidents.

	Mean (1)	Median (2)	St. dev. (3)	N of obs (4)	N of firms (5)
Revenue, $000's	$3,214	$460	$21,164	126,942	51,308
Assets, $000's	$3,058	$143	$42,876	126,942	51,308
Earnings Before Taxes, $000's	$185	$8	$10,169	125,847	51,016
EBT / Revenue	0.038	0.015	0.076	125,847	51,016
Debt / Assets	0.110	0.000	0.225	126,942	51,308
Number of employees	92	29	627	126,942	51,308
Revenue growth	0.111	0.155	0.621	105,672	42,813
Revenue per employee	$36.73	$14.64	$53.67	126,942	51,308
Revenue/Assets	6.864	3.745	8.030	126,942	51,308
Bank receipts	$3,204	$339	$72,175	126,942	51,308
Bank receipts growth	0.198	0.223	0.858	81,010	35,828
Bank receipts per employee	$33.04	$11.00	$53.20	126,942	51,308
Bank receipts/Assets	5.042	2.249	6.898	126,942	51,308
ShadowR	0.090	0.021	0.139	126,942	51,308
Wage transparency	-17.125	-16.974	1.785	54,181	27,762
PTC top 1	4.523	4.780	2.361	75,222	35,107
PTC top 5	4.495	4.436	1.675	118,096	49,301
PTC(2) top 1	4.879	5.494	2.713	62,353	29,584
PTC(2) top 5	4.780	4.768	2.075	110,048	46,656
PTC(3) top 1	4.693	5.074	2.513	72,149	33,966
PTC(3) top 5	4.657	4.623	1.804	116,321	48,844
PTC(4) top 1	4.857	5.168	2.703	56,401	26,974
PTC(4) top 5	4.853	4.815	2.208	102,522	43,938
PTC(5) top 1	4.534	4.772	2.291	2,043	1,180
PTC(5) top 5	4.735	4.823	2.356	7,060	4,183

Table A4. PTC and Firm Performance for Companies without Cars

The table presents the relation of PTC to firm performance for the subsample of companies which do not own cars. The sample period is from 1999 to 2004. All variables are defined in Table A3. The numbers in parentheses are robust standard errors, clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Dependent var:	Revenue growth		Log(Revenue per employee)		Log(Revenue/Assets)	
	(1)	(2)	(3)	(4)	(5)	(6)
PTC top 1	0.0080		0.0101		0.0024	
	(0.0011)***		(0.0016)***		(0.0007)***	
PTC top 5		0.0131		0.0135		0.0035
		(0.0012)***		(0.0019)***		(0.0008)***
Debt/Assets	-0.0506	-0.0512	0.1464	0.1644	-0.0419	-0.0504
	(0.0131)***	(0.0105)***	(0.0175)***	(0.0148)***	(0.0089)***	(0.0074)***
Assets decile dummy	Y	Y	Y	Y	Y	Y
Revenue decile dummy	Y	Y	Y	Y	Y	Y
Industry dummy	Y	Y	Y	Y	Y	Y
Year dummy	Y	Y	Y	Y	Y	Y
Tax district dummy	Y	Y	Y	Y	Y	Y
R-sq	0.033	0.031	0.601	0.598	0.900	0.899
Number of obs	62,656	98,233	75,222	118,096	75,222	118,096
Number of firms	29,227	41,112	35,107	49,301	35,107	49,301

Table A5. Firm Performance and Different PTC Measures

The table presents the relation of different PTC measures to firm performance. The sample period is from 1999 to 2004. *Revenue*, *Debt*, *Assets* are taken from Rosstat. *Revenue growth* is defined as [log($Revenue_{t+1}$)-log($Revenue_t$)]. All other variables are defined in Table 2. Panel A presents regressions of *Revenue Growth*, Panel B shows regressions of Log(*Revenue per employee*), and Panel C presents regressions of Log(*Revenue/Assets*). PTC(2) is calculated only for drivers from the city of Moscow. PTC(3) is estimated for the subsample of drivers for which distance to work is determined. PTC(4) is calculated only for drivers from Moscow which own a car. PTC(5) is estimated only for drivers with a positive record of traffic accidents. The numbers in parentheses are robust standard errors, clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Panel A. Revenue growth and different PTC measures

Dependent var:	Revenue Growth			
PTC(N) var:	PTC(2)	PTC(3)	PTC(4)	PTC(5)
	(1)	(2)	(3)	(4)
PTC(N) top 5	0.0086	0.0110	0.0083	0.0073
	(0.0009)***	(0.001)***	(0.0009)***	(0.0033)**
Debt/Assets	-0.0291	-0.0247	-0.0248	-0.0323
	(0.0099)***	(0.0096)**	(0.0102)**	(0.0401)
EBT/Revenue	0.1953	0.2057	0.2056	0.0152
	(0.0251)***	(0.0247)***	(0.0259)***	(0.1069)
Log(Revenue)	-0.0914	-0.0922	-0.0922	-0.1079
	(0.0023)***	(0.0022)***	(0.0024)***	(0.0091)***
Assets decile dummy	Y	Y	Y	Y
Revenue decile dummy	Y	Y	Y	Y
Industry dummy	Y	Y	Y	Y
Year dummy	Y	Y	Y	Y
Tax district dummy	Y	Y	Y	Y
R-sq	0.032	0.032	0.032	0.054
Number of obs	114,536	120,531	107,170	7,221
Number of firms	46,514	48,503	44,017	4,188

Panel B. Log(Revenue per employee) and different PTC measures

Dependent var:	Log(Revenue per employee)			
PTC(N) var:	PTC(2)	PTC(3)	PTC(4)	PTC(5)
	(1)	(2)	(3)	(4)
PTC(N) top 5	0.0135	0.0147	0.0198	0.0108
	(0.0015)***	(0.0017)***	(0.0015)***	(0.0047)**
Debt/Assets	0.1405	0.1337	0.1386	0.0423
	(0.0149)***	(0.0144)***	(0.0154)***	(0.049)
EBT/Revenue	-0.2100	-0.2038	-0.1984	-0.2532
	(0.0448)***	(0.0438)***	(0.0461)***	(0.1556)
Log(Revenue)	0.6726	0.6749	0.6711	0.6526
	(0.0044)***	(0.0042)***	(0.0046)***	(0.0128)***
Assets decile dummy	Y	Y	Y	Y
Revenue decile dummy	Y	Y	Y	Y
Industry dummy	Y	Y	Y	Y
Year dummy	Y	Y	Y	Y
Tax district dummy	Y	Y	Y	Y
R-sq	0.574	0.575	0.574	0.601
Number of obs	136,051	143,485	127,067	8,693
Number of firms	55,182	57,635	52,159	5,064

Panel C. Log(Revenue/Assets) and different PTC measures

Dependent var:	Log(Revenue/Assets)			
PTC(N) var:	PTC(2)	PTC(3)	PTC(4)	PTC(5)
	(1)	(2)	(3)	(4)
PTC(N) top 5	0.0022	0.0029	0.0035	0.0007
	(0.0006)***	(0.0007)***	(0.0006)***	(0.002)
Debt/Assets	-0.1527	-0.1501	-0.1529	-0.1305
	(0.0079)***	(0.0076)***	(0.0082)***	(0.0261)***
EBT/Revenue	-0.5594	-0.5543	-0.5657	-0.5042
	(0.0265)***	(0.0252)***	(0.0275)***	(0.0883)***
Log(Revenue)	0.7093	0.7114	0.7078	0.7215
	(0.0048)***	(0.0044)***	(0.005)***	(0.0118)***
Assets decile dummy	Y	Y	Y	Y
Revenue decile dummy	Y	Y	Y	Y
Industry dummy	Y	Y	Y	Y
Year dummy	Y	Y	Y	Y
Tax district dummy	Y	Y	Y	Y
R-sq	0.890	0.891	0.889	0.895
Number of obs	136,051	143,485	127,067	8,693
Number of firms	55,182	57,635	52,159	5,064

Table A6. Cardinal PTC and Firm Performance

The table presents the relation of cardinal PTC to different measures of firm performance. Cardinal PTC is calculated for every individual as the residual from regression (1). The sample period is from 1999 to 2004. *Revenue, Debt, Assets* are taken from Rosstat. *Revenue growth* is defined as [log($Revenue_{t+1}$)-log($Revenue_t$)]. All other variables are defined in Table 2. Panel A presents estimations with the same firm-level controls as in Table 4. A possible reason for a weak statistical significance in columns (3)-(6) may be due to the inclusion of both asset and revenue decile dummies, which explain a high fraction of the variance of the dependent variable. Thus, Panel B shows estimations when revenue decile dummies are excluded from firm-level controls. The numbers in parentheses are robust standard errors, clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Panel A. Cardinal PTC and firm performance. All firm-level controls

Dependent var:	Revenue growth		Log(Revenue per employee)		Log(Revenue/Assets)	
	(1)	(2)	(3)	(4)	(5)	(6)
Cardinal PTC top 1	0.1454		0.0470		0.0071	
	(0.0273)***		(0.041)		(0.0168)	
Cardinal PTC top 5		0.2000		0.0501		0.0288
		(0.029)***		(0.0448)		(0.0181)
Debt/Assets	-0.0487	-0.0427	0.1935	0.2042	-0.0469	-0.0575
	(0.0118)***	(0.0094)***	(0.0167)***	(0.0141)***	(0.0084)***	(0.007)***
Assets decile dummy	Y	Y	Y	Y	Y	Y
Revenue decile dummy	Y	Y	Y	Y	Y	Y
Industry dummy	Y	Y	Y	Y	Y	Y
Year dummy	Y	Y	Y	Y	Y	Y
Tax district dummy	Y	Y	Y	Y	Y	Y
R-sq	0.033	0.030	0.579	0.576	0.895	0.894
Number of obs	78,039	122,434	92,722	145,695	92,722	145,695
Number of firms	35,100	48,948	41,756	58,157	41,756	58,157

Panel B. Cardinal PTC and firm performance. Revenue deciles are excluded.

Dependent var:	Revenue growth		Log(Revenue per employee)		Log(Revenue/Assets)	
	(1)	(2)	(3)	(4)	(5)	(6)
Cardinal PTC top 1	0.1241		0.1889		0.1567	
	(0.0268)***		(0.0544)***		(0.0406)***	
Cardinal PTC top 5		0.1846		0.1522		0.1367
		(0.0287)***		(0.058)***		(0.0432)***
Debt/Assets	-0.0065	-0.0020	-0.0924	-0.0821	-0.3465	-0.3614
	(0.0116)	(0.0092)	(0.0224)***	(0.0187)***	(0.0182)***	(0.0149)***
Assets decile dummy	Y	Y	Y	Y	Y	Y
Industry dummy	Y	Y	Y	Y	Y	Y
Year dummy	Y	Y	Y	Y	Y	Y
Tax district dummy	Y	Y	Y	Y	Y	Y
R-sq	0.009	0.009	0.279	0.286	0.543	0.544
Number of obs	78,039	122,434	92,722	145,695	92,722	145,695
Number of firms	35,100	48,948	41,756	58,157	41,756	58,157

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Appendix B – Legitimacy of the Data Used in the Paper

This paper relies on several data sources (banking transaction data, personal income data, traffic violation data, and other data) leaked to the public domain from the Russian Central Bank and other government-affiliated entities. These data are available both for free and for a modest payment from several websites: www.rusbd.com, www.wmbase.com, www.mos-inform.com, www.specsoft.info, and www.gibdd-base.info, among others.[13] These websites primarily charge for the service that they provide by formatting the datasets to make the data more easily accessible rather than for the provision of data itself, which are also available for free.[14] The Russian media have widely discussed the incident of the appearance of the various government databases in the public domain.[15] As the data became available to the public, presumably without official permission from the Russian authorities, it is important to note that the Russian government and Russian Central Bank are aware of the usage of these data by journalists and researchers and publicly discuss policy-relevant conclusions of the analyses based on the data. For instance, I was invited to present an early version of the Mironov (2013) paper at the government-sponsored conference on tax evasion in October of 2006 in Moscow.[16] In addition, I received a request from the First Deputy Chairman of the Central Bank of Russia, Andrei Kozlov, and a Deputy Chairman, Viktor Melnikov, to write a policy memo explaining the methodology of identifying fly-by-night firms developed by Mironov (2013). In this request, top Central Bank officials refer to "the banking transaction data from the Internet" as a legitimate source of information and acknowledge that the research department of the Central Bank uses

[13] The data for this research were purchased from www.rusbd.com.

[14] For example, www.gibdd-base.info charges $4 for a full set of information that is present in all GIBDD (Russian road traffic police) databases on any given individual.

[15] See, for instance, Forbes (2004) and the publication in the most influential Russian daily "Vedomosti" - Vedomosti (2004). Several subsequent articles discuss the authenticity of banking transaction data and personal income data (e.g., Vedomosti (2005a) and Vedomosti (2005c)).

[16] Mironov (2013) relies on a number of data sources, including banking transaction data, personal income data, the city of Moscow's auto registration database, and a police database of lost and stolen identifications.

the same data.[17] The fact that the government and the Central Bank officials take the results of research based on these data seriously is an indication of the reliability of these data.

Both journalists and researchers actively use these data in their publications. For an example of a journalist investigation using these data, see Vedomosti (2005b); for popular descriptions of research based on these data, see Smart Money (2006a,b), Vedomosti (2011), Harvard Business Review (2012), and the Wall Street Journal (2013). For academic research based on these or similar data sets, see Braguinsky, Mityakov, and Liscovich (2010), Braguinsky and Mityakov (2013), Guriev and Rachinsky (2006), Mironov (2013), Mironov and Zhuravskaya (2012), among other works. No lawsuits have been initiated against any party for using these data despite the wide circulation of the data and media publications on them. When commenting in the press on the leakage of the banking transaction data, lawyers within the Ministry of Interior of the Russian Federation explained that the Russian Central Bank never admitted that any data were leaked from the Bank; therefore, from a legal standpoint, all data sets in the public domain are legal, and no dataset is considered illegitimate.[18] The same is true for other similar databases: the Russian government never acknowledged that any data were leaked, and no investigations of this matter were initiated. Vladimir Babkin, an economist with the Russian Central Bank, explains the phenomenon of the leakage of these data by noting the excessive regulation of secrecy and the lack of financial transparency regulations; he argues for the need to officially make the data public (Bank Review, 2005).

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Appendix C – Identification of Spacemen

This section provides a short summary of procedures developed by Mironov (2013). I discuss here what a “fly-by-night firm” is and how they are identified.

The income diversion schemes typically involve the artificial inflation of expenses through fake contracts. For example, firm A wants to evade $X so it makes a deal with firm B to render goods or services of value of $100, but firm A pays firm B $100 + $X. Firm B pays $100 to a real supplier (firm C) that delivers goods or services, and firm B returns $X to firm A's manager or owner. Firm B, referred to as a *spaceman*, comes from seemingly nowhere, does not perform any real activities, pays almost no taxes, and disappears ("flies into space") in a short period of time. This type of firm is also called a "dump," "flashlight," "bruise," "hedgehog," "fly-by-night company," or a “one-day-company.” According to Sergei Arkelov, the deputy head of the Federal Tax Service, spacemen generally do not submit accounting statements to authorities (Interfax, 2011). Diversion of corporate funds using spacemen often involves long chain of transactions, with each transaction appearing to be legitimate. Spacemen are typically registered in the names of homeless people or persons whose identification has been lost or stolen. Spacemen are also often registered in the names of people who sell their identification data. As it was revealed during several interviews with business executives in Moscow that in 2003 to 2004, the costs of creating a new spaceman were about $350 to $500, and law firms that specialize in registering new businesses often sell spacemen that are already registered.

Because $X can be large and is usually paid in cash, spaceman schemes require the collaboration of bank officials. As the Wall Street Journal reports, “In the West, most business payments are made by bank transfer, and cash withdrawals of even a few thousand dollars can raise eyebrows. In Russia, cash is king. Companies–both criminal and outwardly legitimate–often use it to pay salaries, and so avoid onerous payroll taxes… To get their hands on that money, businesses must navigate strict rules barring banks from dispensing large amounts of cash. Luckily for them there are dozens of small, fly-by-night banks ready to use legal loopholes–and panoply of complex financial scams–to get around the rules. For the banks, which charge fees of as much as 5% for customers to withdraw cash, it is a lucrative business." (Wall Street Journal, 2006).

Income diversion can be used to save on taxes as well as to divert funds for personal use by managers or owners. How much do companies save in taxes from spaceman schemes? Consider the case of a company that transfers $100 to a spaceman for fake services, and this money is returned to the company's owner. The spaceman provides an invoice for $84.75 (services) + $15.25 (VAT, 18%), totaling $100. The company can then decrease its total VAT payment by $15.25 (VAT already "paid" by the spaceman). Next, the company is allowed to decrease its taxable income by $84.75 (the cost of "services" provided by the spaceman), which yields a profit tax savings equal to $20.34 (=$84.75*24% (the profit tax rate)). If the company had paid all appropriate taxes on the $100, the amount left for the company to return to its owner would be $64.41, not $100. Further, if the company paid $64.41 as a dividend, the owner would have to pay a dividend tax of $5.80 ($64.41*9% (the dividend tax rate)). Thus, if a firm uses a spaceman to hide its $100 profit, then the total tax evasion would be $41.39 ($15.25+$20.34+$5.80), or 41.39% of the money transferred to the spaceman. Another popular way of using spacemen money is payment of an under-the-table salary, thereby avoiding payroll taxes. In this case, companies evade social security tax (30.4%), VAT (18%), and personal income tax (13%). Thus, the total tax savings is 49.51% of the money transferred to the spacemen. Finally, a company might use money transferred to spacemen to pay cash expenses because some suppliers, especially small businesses, offer substantial discounts for cash payments, which allow the suppliers to hide these cash receipts from the tax authorities. By using spacemen money to pay cash expenses, a firm evades VAT on the amount of VAT paid by spacemen.

The same schemes can be used not only for tax evasion but also for managerial diversion. William Browder, CEO of Hermitage, believes that "Gazprom [is] destroying shareholder value through …the increased use of secretive intermediaries, whose relationships with the company remained unknown." (The Times, 2005). Many investors agree with Mr. Browder that large companies use spacemen primarily for managerial diversion rather than for tax evasion. Indeed, if a manager transfers some of the firm's profits to spacemen, then these profits are hidden not only from the government but also from minority investors.

Empirically, the spacemen are identified as firms that pay no or negligible taxes. Using the banking data, any transfer to a tax collection agency is considered as a tax payment.[19] A firm is defined as a spaceman if it satisfies all of the following criteria: (a) the ratio of taxes paid to the difference in cash inflows and outflows (net tax rate) is less than 0.1%; (b) the firm pays less than 216 rubles ($7.2) in SST per month, which corresponds to one minimum wage;[20] and (c) the firm's cash inflows are higher than its outflows. In Russia, even a loss making firm must pay VAT, SST, and property taxes; hence, these criteria guarantee that such a firm cannot survive even a simple examination by tax authorities. A firm's gross tax rate is defined as

$$gross\ tax\ rate = \frac{tax\ paid}{\left(cash\ inflow + cash\ outflow\right)/2}.$$

Because the price for spaceman services in 2003 started as low as 1%, the nature of their business prevents such firms from paying taxes that are higher than 1% of average turnover. Therefore, a firm is classified as *regular* if it has a gross tax rate of more than 1%; firms with tax rates between 0.1% and 1% represent a mix of spacemen and regular firms and therefore are not attributed to either class.

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[19] This potentially leads to an overestimation of a firm's tax burden. For example, if a local tax office sublets part of its building to a cafe, then each rental payment made by the cafe will be treated as a tax payment.
[20] In 2003 to 2004, the official minimum wage in Russia was 600 rubles ($20).

I triangulate the spacemen identification method in a few ways. The monthly turnover of a spaceman is over 2.5 times greater than that of a regular firm ($641,535 versus $251,247) but performs 40% fewer transactions (25 versus 42); therefore, an average spaceman transaction is 4.3 times higher than an average regular firm transaction. Furthermore, a spaceman exists almost 200 days fewer than a regular firm (391 days versus 588 days), where firm age is defined as the date of the last transaction minus the date of the first transaction in the sample.

Next, the data on spacemen and regular firms are matched to Rosstat – Russian official statistical agency. The results of this match indicate that 43.4% of spacemen are not found in the Rosstat database (i.e., they never provided any reports to Rosstat) as compared to 9.5% of regular firms. Only 34.7% of spacemen reported positive revenue for 2003 or 2004. Of these 34.7% spacemen, the average (median) spaceman reported $2,433K ($9.3K) of revenue, even though its banking receipts were $13,630K ($2,630K). These statistics contrast with those of regular firms: 69.9% of regular firms reported positive revenue in 2003 or 2004. An average (median) regular firm reported $3,586K ($390K) of revenue, and it received $2,866K ($450K) of inflow in its bank account. Firm registry data indicate that spacemen are often registered at a "mass registration" address i.e., an address at which many other companies are also registered; 69.9% of spacemen are registered at addresses where at least 100 other firms are registered, and 28.4% of spacemen are registered at addresses where at least 500 other firms are registered (for regular firms, the respective statistics are 38.6% and 14.3%). Identification data on 18.9% of spacemen CEOs are present in the police database of lost and stolen identifications. According to the Moscow auto registry data, 17.8% of spacemen CEOs own (or ever owned) a car, and 13.9% earned more than $1 per day ($365 per year). A person is defined as "poor" if he or she never owned a car and has income below $1 per day. According to this definition, 73.7% of spacemen CEOs can be classified as poor. In comparison, the average CEO of a regular firm has a reported income that is four times higher than that of the average CEO of a spaceman and is three times more likely to own a car.[21] The data for the owners of spacemen exhibit a similar pattern. Compared to the owners of regular firms, an average spaceman owner earns an income that is six times lower and is one-third as likely to own a car. Even though the CEOs and owners of spacemen are much poorer than those of regular firms, the average receipts of spacemen are about five times greater than those of regular firms ($13,631K vs. $2,866K). This evidence suggests that the nominal CEOs and owners of spacemen are not the real ones.

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Appendix D – Description of Variables Used in the Analysis

D.1 Sample of Drivers

The sample period is from 1997 to 2007.

- *Traffic violations per year* – the average number of traffic violations per year committed by an individual in the city of Moscow and Moscow region. It is calculated as the total number of traffic violations divided by 11 if the person's driver license was issued before 1997. If the person's driver license was issued after

[21] Note that an average income is calculated only for persons with positive income. Because twice as many "regular" CEOs have positive income in 2002 than spaceman CEOs, the true difference in income between regular CEOs and spaceman CEOs is about eight times.

1997, then *Traffic violations per year* is calculated as the total number of traffic violations divided by (2007 – *the year the person's driver license was issued* +1).

- *Traffic accidents per year* – the average number of traffic accidents per year committed by an individual in the city of Moscow. It is calculated as the total number of traffic accidents divided by 11 if the person's driver license was issued before 1997. If the person's driver license was issued after 1997, then *Traffic accidents per year* is calculated as the total number of traffic violations divided by (2007 – *the year the person's driver license was issued* +1).
- *Driver is from Moscow* – a dummy variable equal one if the person resides in the city of Moscow.
- *Male* – a dummy variable equal one for men and zero for women.
- *Driver's age* – the average driver's age. It is calculated as the average age over the sample period if the person's driver license was issued before 1997. If the person's driver license was issued after 1997, then *Driver's age* is calculated as the average age over the period from *the year the person's driver license was issued* to 2007.
- *Driving experience* – the average driving experience. It is calculated as the average driving experience (i.e. the difference between the current year and *the year the person's driver license was issued*) over the sample period if the person's driver license was issued before 1997. If the person's driver license was issued after 1997, then *Driving experience* is calculated as the average driving experience over the period from *the year the person's driver license was issued* to 2007.
- *Income* – the average person's income taken from the personal income data of Moscow residents. The personal income data covers the period from 1999 to 2004
- *Distance to work* – a straight line between person's home zip code and his or her employer zip code averaged over the period from 1999 to 2004 (i.e. the period when

the employment information is available). *Distance to work* is obtained for 2,235,680 observations.

- *Driver owns a car* – a dummy variable equal one if the person ever owned a car during the sample period (car registry is available only for the city of Moscow).
- *Car age* – the average car age calculated over the period when the person owned a car or cars.
- *Car power* – the average car power calculated over the period when the person owned a car or cars.

All variables are winsorized at the top 1% percentile.

D.2 Sample of Companies

The sample period is from 1999 to 2004.

- *Revenue* – firm's book revenue taken from Rosstat.
- *Assets* – firm's book assets taken from Rosstat.
- *Earnings Before Taxes* – firm's book earnings before taxed taken from Rosstat.
- *Debt* – a sum of firm's short term debt and long term debt. Both are taken from Rosstat.
- *Number of employees* – the number of firm's employees obtained from the personal income data of Moscow residents.
- *Bank receipts* – the total cash receipts obtained from the banking transaction data.
- *Revenue growth* – firm's revenue growth calculated as [log$(Revenue_{t+1})$ – log$(Revenue_t)$].
- *Bank receipts growth* – firm's bank receipts growth calculated as [log$(Bank\ receipts_{t+1})$ –log$(Bank\ receipts_t)$].

- *ShadowR* – the measure of income diversion developed by Mironov (2013). It calculated as *Transfers to fly-by-night firms ("spacemen")* divided by *Revenue.* See Appendix C for details.
- *Wage transparency* – the measure of income transparency developed by Braguinsky and Mityakov (2013). Braguinsky and Mityakov construct their measure of wage transparency based on the difference between a person's reported income and the value of the car that he or she drives. Their approach to measure the wage transparency is based on the idea that it is relatively easy to misreport earnings but costly to drive an unregistered vehicle. Therefore the discrepancy between the reported income and car value reflects the person's unreported income. Braguinsky and Mityakov obtain the car values using the price information from the two large auto-trading websites that were operating in Moscow during 2005 and 2006: www.autonet.ru and www.automosk.ru. A person's reported income is obtained from the personal income data of Moscow residents. Then, Braguinsky and Mityakov measure income transparency at a personal level as

$$Transparency_t^i = \log\left(Income_t^i\right) - \frac{1}{\lambda}\log\left(Car_t^i\right)$$

  where *t* is the time index and *i* is the person index. $Income_t^i$ is the person's reported income, Car_t^i is the dollar value of the person's car, and λ is the demand elasticity for cars estimated at 0.35. *Wage transparency* is calculated as the average *Transparency* of the firm's employees.

To reduce the effect of outliers, all variables used in the analysis are winsorized at the top and bottom 5% level. Specifically, the following variables are winsorized: *Revenue growth*, *Bank receipts growth*, Log*(Revenue per employee)*, Log*(Bank receipts per employee)*, Log*(Revenue/Assets)*, Log*(Bank receipts/Assets)*, *Debt/Assets*, *ShadowR*, and *Wage Transparency*.

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